Solar PV Technology Adoption in the United States:
An Empirical Investigation of State Policy Effectiveness

Christine Lasco Crago, University of Massachusetts Amherst, ccrago@resecon.umass.edu
Ilya Chernyakhovskiy, University of Massachusetts Amherst, ichernya@umass.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Solar PV Technology Adoption in the United States: An Empirical Investigation of State Policy Effectiveness

Christine Lasco Crago* and Ilya Chernyakhovskiy

Abstract

State policy incentives for solar power have grown significantly in the past several years. This paper uses county level panel data to investigate whether state policy incentives are effective in increasing residential solar PV capacity. Empirical findings show that tax incentives, rebates, solar-specific mandates, and loan financing programs are important drivers of residential PV adoption. These results suggest that policy incentives play a significant role in encouraging wider use of solar energy. Results also point to a significant positive relationship between hybrid vehicle sales and residential PV adoption, indicating the importance of pro-environmental preference as a predictor of solar PV demand.

Renewable energy has received growing support in the past several years due to concerns about climate change and energy security. Solar photovoltaic (PV) technology is one of the most promising sources of renewable energy (RE). Solar energy resource is widely abundant in the United States, and solar power generation produces less greenhouse gas emissions relative to energy sources from fossil fuels. According to Lopez et al. (2012), customer-cited rooftop solar PV has the technical potential to supply roughly 20% of annual electricity demand in the United States. In 2010 the United States federal government spent $1.1 billion in financial support for solar energy development, representing more than a 5-fold increase from 2007 levels.[1] States have also played a larger role in incentivizing renewables like solar by establishing mandates broadly for renewable energy and specifically for solar. In addition to solar energy generation goals and mandates, generous financial incentives in the form of rebates and tax credits and exemptions are being offered. In the case of residential applications, these financial incentives have lowered the cost of installing a solar photovoltaic (PV) system by as much as 50%. Given the large amount of current and projected government expenditures that go to solar incentive programs, it is important to determine what types of incentives are effective, and to what extent they influence solar adoption.

*Corresponding author. Assistant Professor, Department of Resource Economics, University of Massachusetts Amherst. Address: 217C Stockbridge Hall, 80 Campus Center Way, Amherst, MA 01003. Phone: +1 413 545-5738. Email addresses: ccrago@resecon.umass.edu (C.L. Crago), ichernya@umass.edu (I. Chernyakhovskiy).

[1]United States' federal spending to promote renewable energy technology totalled $14.7 billion in 2010, growing significantly from its level of $5.1 billion 2007. In comparison, federal spending to promote wind power totalled $4.98 billion in 2010 and $476 million in 2007 (U.S. Energy Information Adiminstration (EIA) 2011).

Despite the fact that incentives for solar PV have become widespread, there are few empirical studies that examine the effectiveness of specific policies used to incentivize residential solar PV adoption. To date, there is no empirical investigation of the impact of solar PV incentives that parses the effects of different state policies. This paper fills this gap in the literature.

We use county level data spanning eight years (2005-2012) to examine the impact of state policy incentives for residential PV while controlling for demographics, solar resources, and environmental preferences using panel data estimation methods. Newly installed residential solar PV capacity in kilowatts (kW) is the dependent variable of interest.

This paper improves upon the existing literature examining determinants of solar adoption in a number of ways. First, individual representation of policies enables us to investigate the effectiveness of different policy options. Existing studies that examine the drivers of residential solar energy adoption (solar hot water or PV) either lump policy incentives in one variable (Kwan 2012) or do not consider them (Zahran et al. 2008). Second, we use panel data to examine the impact of specific incentives on adoption. Previous studies (Kwan 2012; Zahran et al. 2008) rely on cross section data which, while informative, does not exploit variation over time. We use random effects and pooled Tobit models to estimate the relationship between residential PV capacity and a set of explanatory variables. Third, we use a rich set of environmental preference controls including the percentage of county residents that buy organic foods, voting rates for the Democratic Party, and sales of hybrid vehicles. Other studies typically use only voting behavior in Presidential elections or support for a particular environmental regulation to measure environmental preference. Kwan (2012) and Zahran et al. (2008) use participation in the International Council for Local Environmental Initiatives (ICLEI) as proxy for environmental preference. We use hybrid vehicle ownership rates, following from recent findings that capitalization of solar PV enabled homes is higher in communities with a greater share of hybrid vehicles (Dastrup et al. 2012). To our knowledge this is the first paper to jointly use these different aspects of consumption preferences and voting behavior to account for environmental preferences.

Our empirical results show that policy incentives are effective at increasing solar PV capacity at the county level. Sales tax exemptions and income tax credits, rebate availability and loan financing programs are significantly related to increases in PV capacity per county. Solar energy credit markets and stringency of solar generation mandates are also found to significantly increase residential solar PV capacity. Unlike previous studies, we find little evidence that education level and age are significant. These results suggest that policy incentives play a significant role in increasing the demand for solar energy, while previous findings about the effects of demographics are not well supported. Results also indicate that Democratic party affiliation as well as demand for hybrid vehicles are positively related to solar PV adoption, suggesting the importance of environmental preferences in residential solar PV decisions.

The paper proceeds as follows: section 1 gives a brief background of solar policy incentives at the state level. Sections 2 presents our analytical framework and section 3 discusses the empirical model. Section 4 presents data sources. Section 5 discusses our empirical findings and section 6 concludes.

1 Background

Over the last several years, solar PV technology has enjoyed a steep upward trend in adoption across the United States (U.S.). Total operating solar PV capacity reached 12.1 GW by the end of 2013. In 2012 the U.S. was fourth in the world PV market for total peak power capacity behind Germany, Italy and China (Barbose, Darghouth, and Wiser 2012). Net electricity generation from solar power sources has grown exponentially; between 2009 and 2013 annual net generation increased by roughly 5000% (U.S. Energy Information Adiminstration (EIA) 2014). New solar capacity additions in 2013 totalled 4,751 MW, a 41% increase over 2012 additions. In 2013 solar capacity additions overtook wind energy as the second-largest source of new energy generating capacity behind natural gas (U.S. Energy Information Adiminstration (EIA) 2014).

Residential solar PV systems represents an important market segment. In 2013, 792 MW of new capacity was added, representing 17% of solar capacity additions that year. Forecasts of solar PV capacity additions in 2014 project growth to be most rapid in the residential segment (GTM Research and Solar Energy Industries Association 2014).

Concurrently, solar power industry revenues, employment, and wages have increased steadily since 2007, with a strong upward trend projected to continue uninterrupted through 2018 (Smith 2013). However, while the U.S. solar power industry has enjoyed substantial growth in recent years, the share of solar generated electricity is small when compared with other energy sources. Electricity generated from solar energy accounted for only 0.2% of total electricity generated in the U.S. in 2013 (U.S. Energy Information Adiminstration (EIA) 2014).

1.1 State policy incentives

State governments have implemented a range of policy initiatives aimed at increasing the share of solar PV-generated electricity in the U.S. energy mix. In 2011 alone, legislatures in ten states enacted various innovative financial incentives directed at increasing in-state residential PV capacity (DSIRE 2013). Renewable portfolio standards have received the most attention in case studies and empirical analyses. Renewable portfolio standards (RPS) are regulations which mandate that a specific share of a state's electricity sales must be generated from RE sources. Carley (2009) and Yin and Powers (2010) show empirically that RPS implementation is associated with positive growth of in-state RE generation. Findings by Maguire (2011) and Adelaja et al. (2010) provide evidence that RPS positively influence wind energy adoption. However, Carley (2009) points out that RPS generally fail at achieving their stated goal of increasing the share of RE generation in a state's total energy mix. In a descriptive analysis of states' experiences with RPS policies thus far, Wiser, Barbose, and Holt (2011) emphasize the need to include technology-specific standards into RPS designs to promote diversity in RE markets. The authors cite evidence that RPS alone promote only a limited number of least-cost renewable technologies. While solar PV technology is a promising source of renewable energy, the currently high cost of solar panels does not make it competitive with wind energy, hydropower or geothermal. One strategy has been to amend existing RPS mandates to include a "carve-out" for solar energy generation. Of the 29 states plus the District of Columbia with active RPS policies, 16 states and the District of Columbia have included a solar carve-out. New Jersey currently has the most aggressive support for solar energy with a carve-out of 4.1% of electricity sales by 2028.

Generally a solar carve-out goes hand in hand with a solar renewable energy credit (SREC) market. An SREC market provides a financial production incentive to solar-enabled households. SRECs are solar energy production credits awarded per kilowatt hour (kWh) to owners of grid-connected solar PV systems. Aggregation firms sell bundles of SRECs to utilities in the state's renewable energy credit market. Utilities are obligated to meet solar energy sales requirements either by installing their own solar power facilities, buying SRECs in the open market, or paying year-end alternative compliance payments. Two variables are used in this study to measure the effects of a state's solar carve-out: the average SREC price per year, and the alternative compliance payment, in dollars per kWh, which is levied on utilities when they fall short of the requirement.

Additional state incentives come in the form of tax policies, cash rebates, and solar consumer support laws. Tax incentives are designed to reduce the high up-front costs of installing a solar PV system. Tax credits, deductions, and exemptions from personal, property, and sales taxes aim to reduce the tax liability of adopters. Many states use a combination of tax-based incentive mechanisms. Roughly twenty states offer sales tax exemptions for the cost of solar equipment, thirty states offer property tax exemptions for the added value to homes with solar PV systems, and twenty states and the District of Columbia provide income tax credits.

Rebate programs provide direct cash subsidies towards the up-front costs of installing a solar PV system, often awarded on a dollar per system kW capacity basis. Rebates are more politically charged than other incentives as they require appropriation of state funds. Sixteen states and the District of Columbia currently have active rebate programs. In Massachusetts, the Commonwealth Solar Rebate II program is allotted $4 million per year since 2003, funded by a $0.0005 per kWh surcharge on electricity bills in the state. In addition to direct financial incentives, states also provide legislative support which can protect solar PV consumers. Solar rights policies are state laws which prohibit local governments from enacting regulations or ordinances restricting a home owner's ability to install a solar energy system.

Table 1.1 gives an overview of when key policies were enacted in the states included in this study. Success with promoting residential solar PV adoption varies significantly across state lines. As of December 2012, New Jersey had a total of 955.7 megawatts (MW) of installed solar PV capacity, whereas New Hampshire ended the year with just 5.4 MW (NREL 2013). After controlling for population size this is roughly a 20-fold discrepancy in solar technology adoption.

It is unclear whether adoption trends are a manifestation of availability of solar resources, i.e., sunshine, individual home-owner characteristics such as income, or genuine responses to state incentive policies. In a county-level study of solar hot water system adoption using cross section data, Zahran et al. (2008) find that age and county participation in the International Council for Local Environmental Initiatives (ICLEI) are significant across model specifications. Policy incentives are not considered in the analysis. Kwan (2012) examines solar PV adoption at the zip-code level using cross section data. He finds that policy incentives have an impact on solar PV adoption. However, Kwan (2012) uses a single aggregate incentives index to represent financial incentives, while mandates, solar consumer rights and

Table 1: State solar PV incentives

Policy	State	Year 2005	2006	2007	2008	2009	2010	2011	2012
Solar carve-out	CT								
	DE			●	●	●	●	●	●
	MA						●	●	●
	MD			●	●	●	●	●	●
	ME								
	NH						●	●	●
	NJ	●	●	●	●	●	●	●	●
	NY†	○	○	○	○	○	○	○	○
	PA		●	●	●	●	●	●	●
	RI								
	VT								
	WV								
Sales tax exemption	CT			●	●	●	●	●	●
	DE								
	MA	●	●	●	●	●	●	●	●
	MD				●	●	●	●	●
	ME								
	NH								
	NJ	●	●	●	●	●	●	●	●
	NY	●	●	●	●	●	●	●	●
	PA								
	RI	●	●	●	●	●	●	●	●
	VT	●	●	●	●	●	●	●	●
	WV								
Rebate	CT								●
	DE	●	●	●	●	●	●	●	●
	MA				●	●	●	●	●
	MD	●	●	●	●	●	●	●	●
	ME	●	●	●	●		●	●	●
	NH						●	●	●
	NJ								
	NY						●	●	●
	PA					●	●	●	●
	RI								
	VT	●	●	●	●	●	●	●	●
	WV								

This table only indicates existence of a policy. Levels of each policy vary by state and time.
†NY's RPS has a customer-cited tier in which solar PV is an eligible technology.

loan financing programs are not considered. He also identifies solar insolation and demographic characteristics such as college graduation rates, age, and income as strong predictors of solar PV adoption.

Active state interest in providing financial incentives for solar PV adoption raises several research questions which have yet to be comprehensively addressed. This paper seeks to answer whether policy incentives are effective at promoting adoption, which incentives are most effective, and what are the prevailing characteristics of homeowners who are likely to invest in a solar PV system.

2 Analytical Model

The analytical model is based on a representative household that seeks to minimize the lifetime cost of a fixed level of electricity consumption by choosing the optimal time to invest in an energy saving device such as a solar PV system. The household minimizes:

$$\int_0^T P_t^E e^{-rt} dt + \int_T^\infty (1-\phi) P_t^E e^{-rt} dt + (1-\pi) I_T e^{-rT} \tag{1}$$

where P_t^E is the price of electricity, ϕ is the proportion of energy generated from solar PV expressed as the ratio of total energy output from solar PV and total electricity consumption, r is the discount rate, I_T is the cost of the solar PV system at the time of installation, and π is the amount of subsidies received as a proportion of I_T. The first term in (1) is the cost of electricity prior to installation of the solar PV system. The second terms is the cost of electricity when the solar PV is in place, and the third term is the installation cost net of subsidies.

The household will make an investment at time T when the following condition holds:

$$\omega = \phi P_T^E - r(1-\pi) I_T \geq 0 \tag{2}$$

Based on equation (2) we can identify the variables that affect the household's decision to install solar PV when economic factors are considered. We expect that factors that increase the value of ω increase the likelihood of adoption by a household at time T, and vice versa.

The higher the price of electricity the greater the likelihood that a household will choose to invest at a given time T. A lower discount rate (r) also encourages investment. Hausman (1979) suggests that there is an inverse relationship between discount rate and income. Thus, we include median home value and income as explanatory variables in our regression. The expectation is that the higher a household's income, the greater the likelihood of adoption.[2]

The share of electricity generated from solar PV (and thus the cost savings attributed to solar PV) is determined in large part by the amount of solar resources available to the household. Thus, we include data on solar insolation. Households with greater access to solar resources will expect greater energy bill savings, reduced payback periods on the investment, and potentially greater returns from production-based policy incentives. We expect that

[2]Income was found to be highly correlated with other demographic variables and was dropped in the final specification.

greater solar insolation would lead to greater likelihood of adoption. In general, the lower the net cost of installing solar PV the greater the likelihood of adoption. The net cost to the household will depend on the amount of financial assistance obtained from solar incentive programs. Thus, we include data on various financial incentives that lower the net cost of PV installation. The installation cost data available through the NREL OpenPV database points to limited variation in installation costs for an average sized residential system (NREL 2013). Residential installation costs are assumed to be constant among counties. A linear time trend variable is included in order to capture changes to federal policies as well as falling prices of solar panels over time.

Equation (2) helps identify financial factors that are likely to affect adoption. However, several studies show that non-economic factors such as the desire to help address environmental externalities, contribute to the public good, gain prestige, and “feel good” about oneself could also motivate solar PV adoption (Andreoni 1990; Sidiras and Koukios 2004; **?**). We use the share of hybrid-electric vehicles in new vehicle registrations per county, percentage of households that purchase organic food, as well as the percentage of Democratric Party votes to represent households’ pro-environmental preferences that cause them to make green investments due to non-financial considerations. Other studies also find that age, urbanization, and educational attainment can be important factors in determining solar adoption (Kwan 2012; Zahran et al. 2008; Lutzenhiser 1993; Labay and Kinnear 1981). It is possible that these variables affect purchasing power, discounting preferences, or environmental awareness. We include median county age and the share of residents with a bachelors degree or higher. As a measure of urbanization we include population density and housing density for each county.

Finally, since the model is explaining decisions over time, residential solar PV capacity in the previous year is included as an explanatory variable for current period capacity additions. As a local PV market develops, competition among installation companies can drive down costs. As more solar panels are installed in a neighborhood, social interactions and solar panel visibility on rooftops may increase homeowners’ propensity to invest in solar PV technology, in effect causing a reduction in perceived uncertainty about solar technology. Homeowners who are on the fence about investing in a costly solar system may be pushed towards adoption by early adopting neighbors.

3 Empirical model and choice of estimation method

The main empirical goal of this paper is to accurately model the drivers of solar PV adoption decisions. As discussed in the literature review, there is not a clear consensus about the drivers of residential solar PV adoption in the US. Several studies point to the importance of demographics and environmental attitudes in solar PV adoption decisions, but responses to state policies have not been thoroughly explored. Equation 3 is the hypothesized linear model of county solar PV capacity additions.

$$Y_{it} = \alpha + X_{it}\beta + Z_i\gamma + K_{it}\kappa + P_{it}\zeta + \epsilon_{it} \tag{3}$$

where Y is the residential solar PV capacity additions in county i in year t and ϵ_{it} is the error vector. Average installed solar kW capacity across all counties and time periods, holding all control variables constant at zero, is captured by the intercept α. The vector X consists of independent variables which vary over time: electricity price, the percent of homeowners with a bachelor degree or higher, the natural log value of median home value, median age, the natural log value of the number of owner-occupied homes, population density, and the percent of new hybrid vehicle sales. Natural log transformations of median home value and the number of owner-occupied homes are taken to normalize the highly right-skewed distributions of their values in levels. Z contains the time-invariant variables: average annual solar resource, percent households that buy organic food, and the percentage of Democratic Party votes in the 2008 presidential election. K contains the state policy variables: sales tax exemption, SREC price, solar alternative compliance payment, and the number of years the RPS has been in effect. P contains the set of binary policy variables indicating availability of the following state incentives and consumer supports: property and personal tax credit, direct cash rebate, solar rights, and loan program. Each term in parameter vector ζ represents the effect of a discrete change from 0 to 1 in the corresponding term in P.

3.1 Limitations of the linear model

In the solar technology adoption context, a potential problem with estimating the linear model in Equation (3) is the high number of counties with no solar installations for a given year. Thirty seven percent of the county-year observations in the data have zero solar capacity additions, and 17% of counties have no solar installations over the entire period. This implies that 37% of linear combinations of explanatory variables included in the model are associated with zero solar PV capacity additions. In this paper we refer to zero values in the dependent variables as a corner solution. The linear model in Equation 3 is problematic because combinations of the right hand side variables may result in negative predictions of solar adoption. Negative values of solar adoption are not reflective of the data generating process. A least squares model will impose a linear association to this data, which is highly non-linear in nature. Thus, parameter estimates obtained from a linear model is likely to be biased and inconsistent.

3.2 Development of the Tobit model

To accommodate a dependent variable with a probability mass point at zero and a continuous distribution in the non-negative range we employ the Tobit model. The Tobit estimator is a maximum likelihood procedure which was originally developed to deal with issues that arise when estimating household decisions to invest in durable goods (Tobin 1958). In more recent econometrics literature and in several textbooks the Tobit model is typically referred to as a censored regression model. One exception is in Wooldridge (2010), in which the author makes a clear distinction between a censored regression Tobit model and a corner solution application of the Tobit estimator. In a censored regression context there are observations in the sample which are artificially censored at some arbitrary point, and the distribution of the observed dependent variable does not accurately reflect the sampling distribution. This contrasts with the context of household investments in durable goods, where expenditures are positive when the utility of investment exceeds an unobserved threshold, and zero otherwise.

The same is true in the solar technology adoption context. Household solar PV capacity additions are strictly positive with a probability mass point at zero. When these decisions are aggregated to the county level the lower limit remains at zero. Zero solar PV capacity addition in a county simply reflects that no new residential solar PV systems were installed in the given year. This is distinct from a censored regression context because the dependent variable is fully observed. The sample fully represents the data generating process, and the observed limit of the data is the true limit of the sampling distribution, i.e., the zeros observed in the dependent variable are true zeros. The linear model in Equation (3) is thus amended to

$$Y^* = X\beta + \epsilon, \quad \epsilon | X \sim \mathcal{N}(0, \sigma^2) \tag{4}$$

where the right hand side variables from Equation (3) are compressed into X and i and t subscripts are suppressed to reduce notational clutter. Y^* is a latent variable which meets the classical linear assumptions and can be interpreted as the desired amount of residential solar PV capacity. The actual values of residential solar PV capacity by county for a given year can be expressed as

$$Y = \begin{cases} Y^*, & \text{if } Y^* > L \\ L, & \text{if } Y^* \leq L \end{cases} \tag{5}$$

where L is the lower limit at zero residential solar PV capacity. With $L = 0$, Equation (5) can also be written as

$$Y = \max\,[0, Y^*] \tag{6}$$

$$Y = \max\,[0, X\beta + \epsilon] \tag{7}$$

Assuming ϵ is normally distributed and orthogonal to $X\beta$, the unconditional expectation can be expressed explicitly as

$$E[Y|X] = \Phi\Big(\frac{X\beta}{\sigma}\Big)X\beta + \sigma\phi\Big(\frac{X\beta}{\sigma}\Big) \tag{8}$$

Several important features of the Tobit model are apparent from Equation (8). The expected value of the dependent variable is not a linear function in the parameters. Simply removing the corner solution observations and proceeding to estimate by OLS is not a valid solution. In addition, the partial effect of an explanatory variable X_j will be a function of β as well as σ. Equation (8) also points to the Tobit model's reliance on a normally distributed and exogenous error term. If ϵ does not meet these assumptions then the Tobit model will provide inconsistent parameter estimates. Maximum likelihood procedure is used to estimate parameters in (8).

3.2.1 Unobserved county heterogeneity as a random effect

To include unobserved heterogeneity by county, both random and fixed effects methods are feasible in the Tobit model context. The fixed effects model is ruled out because it does not allow estimation of coefficients of time invariant explanatory variables. The data for solar insolation and the percentage of democratic votes are both time invariant. Excluding these predictors may cause omitted variable bias. Thus the Tobit MLE is extended to incorporate a random effect.

The linear model for the latent variable is revised, such that

$$Y^*_{it} = X_{it}\beta + \nu_i + \epsilon_{it} \tag{9}$$

where ν_i is the random parameter which represents unobserved county-specific effects and $\nu_i|X_{it} \sim \mathcal{N}(0, \sigma^2_\nu)$, $\epsilon_{it}|X_{it} \sim \mathcal{N}(0, \sigma^2_\epsilon)$. A formal test for random effects is performed using the Breusch-Pagan (BP) Lagrange Multiplier test, which follows a χ^2 distribution. The null hypothesis of no random effect is rejected.

The random effects model maintains strict exogeneity of the error term, where ν_{it} is orthogonal to X_{it} for all i and t, i.e. $cov(\nu_i, X_{it}) = 0$. This is a rather restrictive assumption in that it precludes any autocorrelation in the random effect, so that $cov(\nu_i, X_{it}) = cov(\nu_i, X_{i,t-1}) = 0$ is assumed explicitly. A pooled Tobit model has the advantage of allowing for serial correlation in the error term. In other words, the pooled model is flexible to allow a lagged dependent variable, $Y_{i,t-1}$, to be included as a regressor. A lagged dependent variable may be an important component of the data generating process in that it captures spill-over effects across time periods. For example, homeowners in a community with many visible solar PV installations may be more open to the idea of investing in their own system. Visibility can reduce perceived uncertainty and increase educational social interactions among neighbors. With the inclusion of a time lagged dependent variable, an autocorrelation robust variance-covariance matrix is appropriate for a pooled Tobit model. However, despite potential limitations, a random effects Tobit model is advantageous because it exploits unobserved county-specific heterogeneity in the data. We present results using both the pooled and random effects Tobit model.

4 Data

4.1 Solar Adoption

Data on residential solar PV installations were obtained from the National Renewable Energy Lab (NREL) Open PV Project. The Open PV Project is a public database which provides location and capacity rating information for all solar PV projects in the United States. We obtain data from 2005-2012 for the following states: ME, NH, VT, MA, NY, RI, CT, NJ, PA, DE, MD, WV, and the District of Columbia. Following Barbose, Darghouth, and Wiser (2012) and Kwan (2012), we use an upper limit of 10 kW capacity to denote residential PV systems. Geographic Information System (GIS) software was used to spacially reference and aggregate individual residential PV systems to the county level. County boundary shapefiles were obtained from the U.S. Census Bereau Tiger/Line shapefile database.

4.2 Electricity price and solar resource

Yearly state average electricity prices were obtained from the U.S. Energy Information Administration. Residential electricity prices are averaged yearly for the total electric industry by state, measured in cents per kilowatt hour (¢/kWh). Electricity prices are not indexed or adjusted for inflation.

The average annual solar resource was calculated using data developed by the State University of New York/Albany satellite radiation model. Solar resource, i.e. solar insolation, is measured in kilowatt-hours per square meter per day (kWh/m^2/day). Ten kilometer grid cells of annual average daily total solar resource were spatially referenced and aggregated to obtain annual averages for each county.

4.3 State incentives for solar PV

State policy incentive variables were constructed using the Database of State Incentives for Renewables and Efficiency (DSIRE 2013). State sales taxes are used to capture heterogeneity of sales tax incentive policies. A homeowner receiving a sales tax exemption in a state with a high sales tax effectively receives a larger incentive than an identical homeowner in a neighboring state with a lower sales tax. Personal tax credit and property tax exemptions are included as binary variables, which take on a value of one if the county is located in a state with these incentives. Rebate and loan program availability are also measured as binary variables. Following Menz and Vachon (2006), we also include an RPS trend variable to capture the number of years a state RPS has been in effect. Solar alternative compliance payment (SACP) in dollar amount is included as a measure of solar carve-out stringency. The SACP is a per kWh fine levied on utilities for shortfalls in meeting RPS solar carve-out requirements.

4.3.1 SREC prices

Solar renewable energy credit market prices were obtained from www.SRECtrade.com. One SREC is equivalent to one megawatt hour (MWh) of electricity generation. The market price of SRECs is averaged for each year in the study period. All counties within the same state are subject to the state market price of SRECs. There are some SREC markets which can overlap state lines. For example, the Pennsylvania SREC market accepts energy generated by systems located in Ohio. This effects the market price for solar energy producers located in Pennsylvania.

4.4 Environmental preferences

Three variables are used to capture preferences for positive environmental action. The percentage of county residents who buy organic food was obtained from Geographic Research Inc. (2011). Presidential election results from 2008, obtained from National Atlas of the United States (2009), were used to calculate the percentage of Democratic Party votes by county in the 2008 presidential election. Yearly hybrid vehicle registrations for personal transportation by county were obtained from the consulting firm R. L. Polk.

4.5 Demographic and housing characteristics

County-level yearly data from 2005-2012 on median age, median household income, median home value, number of owner-occupied housing units and total population were from the U.S. Census Bureau's American Community Survey.

Table 2 presents summary statistics of the dependent and independent variables.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Dependent variable				
Capacity additions (kW)	96.716	264.677	0	3583.466
Independent variables				
Solar resource (kWh/m^2/day)	4.491	0.199	4.085	5.007
ln(Owner-occupied homes)	10.379	1.146	7.34	12.908
ln(Population density)	5.428	1.571	1.035	11.18
Electricity price (¢/kWh)	13.898	3.316	6.21	20.33
Bachelor degree or higher (%)	29.757	12.537	3.925	83.252
Median Age	40.202	3.081	27.3	51
ln(Median home value)	12.032	0.591	10.325	13.816
SREC Price ($)	72.013	154.461	0	664.5
Carve-out compliance($)	166.987	243.061	0	711
Sales tax exemption (%)	3.636	3.751	0	8.48
Rebate (d)	0.457	0.498	0	1
RPS trend	4.863	3.54	0	15
Income tax credit (d)	0.349	0.477	0	1
Property tax incentive (d)	0.432	0.495	0	1
Loan program (d)	0.182	0.386	0	1
Solar rights (d)	0.194	0.396	0	1
Hybrid vehicle sales (%)	1.931	1.07	0	10.986
Democrats (%)	51.685	11.92	23.64	92.5
Organic consumers (%)	26.291	4.754	15.72	40.19

(d) for discrete change of dummy variable from 0 to 1.

5 Results and Discussion

This section begins with a table of the estimation results. The results for specifications in Table 3 are estimated parameters obtained by the random effects Tobit maximum likelihood estimator. The signs, magnitudes, and statistical significance of parameter estimates are compared across four different model specifications. A time trend is included in each specification.

Table 3 begins with a "naive" model, by which solar adoption decisions are affected solely by solar resource abundance, electricity prices, income, and demographics. This is akin to the specification used by Zahran et al. (2008) to study the determinants of solar hot water adoption. The next model introduces the set of state policy incentives which are expected to influence adoption decisions. State policies consist of financial incentives (rebates, tax credits, SRECs) and consumer support regulations (loans, access rights). Model (3) adds environmental preference controls. The final specification, Model (4), adds dummy variables for the states in the study region.

Each subsequent specification represents an improvement to the model. The log-likelihood increases from model (1) to model (4) and the pseudo R^2 increases from 25.3% to 32.9%, roughly an 8% increase in explanatory power. Likelihood ratio tests are performed to formally confirm that each subsequent specification is a statistically significant improvement.

Improvements to the model specification reveal significant corrections of bias in the naive model. Omitted variable bias arises when a significant explanatory variable is omitted from the specification. Corrections of omitted variable bias are evident through patterns which emerge as important explanatory variables are introduced with each specification. The effect of solar resource availability more than doubles in magnitude and gains significance when policy variables are introduced in Model (2). Model (2) also shows a large increase in magnitude and gain in significance for educational attainment. College graduates may be more aware of new regulation and positively predisposed to solar technology.

Important differences are also witnessed between Model (2) and Model (3), where environmental preference variables are introduced. The effects of a college education and age lose significance when the environmental preference variables are included in Model (3). The loss of significance for college education may be due to a high linear correlation (0.62-0.79) between environmental preferences and college graduation.

The final specification in model (4) includes dummy variables for each state in the sample. The effect of the state dummy variables is to capture time-invariant differences in county solar adoption due to unobserved heterogeneity at the state level. Two stark differences are witnessed by the inclusion of state dummies. The coefficient of electricity prices plummets and loses significance. However, this result can be understood as an empirical issue which should not be interpreted to reflect the true effect of electricity prices. The data for electricity prices represents state averages over time. The state dummy variables are essentially capturing all cross-sectional variation from the electricity prices, leaving only variation of electricity prices over time. The small parameter estimate and lack of significance suggests that variation in electricity prices over the time period in this study (2005-2012) has had a negligible impact on solar PV adoption. The opposite is witnessed by the parameter estimate for the RPS trend, which takes on a negative significant effect in Model (4). This suggests that the RPS trend variable is correlated with unobserved state-level variables that increase solar PV capacity.

The estimated variance of the random effect, $\hat{\sigma}_u$, has a positive and significant effect which is cut in half in Model (4). The state dummy variables account for time-fixed differences among counties in different states which were previously, in Model (3), being attributed to the county-specific random effect u_i. However, the persistence of significance for the random effect term suggests that there is indeed a significant random effect among counties, even after accounting for differences across state lines.

Table 3: Random effects Tobit MLE Results

Dependent variable ln(PV capacity)	Model (1)	Model (2)	Model (3)	Model (4)
ln(PV capacity)$_{t-1}$	0.310***	0.121***	0.139***	0.185***
	(0.0419)	(0.0357)	(0.0374)	(0.0379)
Solar resource (kWh/m^2/day)	0.276	2.394**	2.463***	1.860**
	(0.682)	(0.747)	(0.748)	(0.708)
ln(Owner-occupied homes)	0.950***	1.135***	1.221***	1.002***
	(0.154)	(0.167)	(0.164)	(0.115)
ln(Population density)	-0.495***	-0.755***	-0.907***	-0.588***
	(0.127)	(0.140)	(0.145)	(0.104)
Electricity price (¢/kWh)	0.344***	0.253***	0.202***	0.0269
	(0.0328)	(0.0439)	(0.0451)	(0.0571)
Bachelor degree or higher (%)	0.00891	0.0427**	0.0108	0.00464
	(0.0136)	(0.0143)	(0.0159)	(0.0114)
Median Age	-0.115***	-0.0717**	-0.0513	-0.0375
	(0.0332)	(0.0343)	(0.0336)	(0.0239)
ln(Median home value)	1.823***	1.356***	1.343***	0.736**
	(0.357)	(0.371)	(0.369)	(0.281)
Time trend	0.382***	0.337***	0.335***	0.675***
	(0.0337)	(0.0439)	(0.0461)	(0.0991)
SREC Price ($)		0.00153**	0.00145**	0.00106**
		(0.000503)	(0.000504)	(0.000526)
Carve-out compliance($)		0.000992**	0.00102**	0.00188***
		(0.000407)	(0.000408)	(0.000486)
Sales tax exemption (%)		0.510***	0.509***	0.377***
		(0.0439)	(0.0433)	(0.0637)
Rebate (d)		0.413**	0.347**	0.354**
		(0.157)	(0.158)	(0.176)
RPS trend		-0.0135	-0.0160	-0.368***
		(0.0353)	(0.0346)	(0.0969)
Income tax credit (d)		1.510***	1.633***	2.142***
		(0.307)	(0.308)	(0.585)
Property tax incentive (d)		-3.105***	-3.006***	-3.167***
		(0.333)	(0.335)	(0.390)
Loan program (d)		2.276***	2.417***	3.166***
		(0.243)	(0.246)	(0.309)
Solar rights (d)		-0.440**	-0.526**	-1.202***
		(0.182)	(0.183)	(0.230)
Hybrid vehicle sales (%)			0.142+	0.374***
			(0.0788)	(0.0740)
Democrats (%)			0.0396***	0.0168**
			(0.0115)	(0.00849)
Organic consumers (%)			0.0409	-0.0170
			(0.0373)	(0.0258)
Constant	-31.99***	-39.25***	-42.09***	-19.55***
	(3.785)	(4.246)	(4.481)	(3.710)
$\hat{\sigma}_u$	1.255***	1.378***	1.309***	0.672***
	(0.110)	(0.104)	(0.105)	(0.0892)
$\hat{\sigma}_e$	1.843***	1.623***	1.625***	1.630***
	(0.0444)	(0.0382)	(0.0386)	(0.0392)
Log-likelihood	-3138.3	-2956.7	-2946.7	-2839.8

Standard errors in parentheses.
(d) for discrete change of dummy variable from 0 to 1.
$^{+}$ $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

5.1 Random effects vs. pooled Tobit

As discussed above, the random effects Tobit model relies on restrictive assumptions about the error terms. Since the model includes a lagged dependent variable, autocorrelation issues in the random effects Tobit model are a concern. The pooled Tobit model has the advantage of being consistent under autocorrelation with autocorrelation-robust standard errors. Table 4 is useful to compare results between pooled Tobit and random effects Tobit models under specifications with and without state dummy variables.

There are some differences in the magnitudes of parameter estimates between the random effects and pooled Tobit models. However, these differences are small in specification (4) that includes state dummies.

5.2 Predictors of residential solar PV adoption

Several explanatory variables are robust to model specification. Lagged capacity additions are significant across specifications, pointing to the existence of a "snowball effect" in residential solar technology adoption. It is reasonable to infer that social interactions and solar panel visibility on neighbors' rooftops may increase homeowners' propensity to invest in solar PV technology. The effect of previously existing solar PV systems can also be interpreted as a reduction in perceived uncertainty about the solar technology.

The number of owner-occupied households in a county has a positive effect and is robust at the 1% significance level. This is primarily a control variable which is used to make comparisons across counties of different sizes. It's significance speaks to the importance of controlling for available roof space. The time trend is also positive and robust to specification. Time effects are assumed to capture changes to federal policies and to solar panel installation costs over time. Costs vary over time due to falling solar panel prices as well as decreasing balance of system (BOS) costs. BOS cost is the industry term for the total cost of installing a solar PV system, including the cost of mounting equipment, interconnection and labor. As the industry develops, experience and competition among installers drive BOS costs downward.

Population density has an inverse relationship with residential solar PV adoption. The negative parameter estimate, robust across specifications at the 1% significance level, indicates a negative relationship between urbanization and residential solar PV adoption. This result is not consistent with Zahran et al. (2008), where empirical evidence pointed to a positive relationship between urbanization and solar hot water adoption. However, the urbanization measure used by Zahran et al. (2008) is a dummy variable for Census-designated urban areas which may include sub-urban environments with relatively low population density when compared with metropolitan city areas.

Of the variables measuring differences in demographics, only median home value is robust to specification. The strong positive result for median home value speaks to the importance of income status as predictor of solar PV adoption. The obvious interpretation is that higher income homeowners have more disposable income to invest in a solar PV system. Estimated effects of educational attainment are weak and sensitive to model specification. Median age in a county has a small negative effect which loses significance when environmental preference variables are introduced.

Table 4: Pooled vs. RE Tobit

	(3)		(4)	
	RE	Pooled	RE	Pooled
ln(PV capacity)$_{t-1}$	0.139***	0.505***	0.185***	0.323***
	(0.0374)	(0.0285)	(0.0379)	(0.0417)
Solar resource (kWh/m^2/day)	2.463***	1.378**	1.860**	1.173**
	(0.748)	(0.448)	(0.708)	(0.533)
ln(Owner-occupied homes)	1.221***	0.791***	1.002***	0.854***
	(0.164)	(0.0919)	(0.115)	(0.113)
ln(Population density)	-0.907***	-0.560***	-0.588***	-0.493***
	(0.145)	(0.0793)	(0.104)	(0.0799)
Electricity price (¢/kWh)	0.202***	0.200***	0.0269	-0.0197
	(0.0451)	(0.0371)	(0.0571)	(0.0618)
Bachelor degree or higher (%)	0.0108	-0.00970	0.00464	-0.00306
	(0.0159)	(0.00933)	(0.0114)	(0.00822)
Median Age	-0.0513	-0.0495**	-0.0375	-0.0323$^+$
	(0.0336)	(0.0197)	(0.0239)	(0.0195)
ln(Median home value)	1.343***	0.745***	0.736**	0.601**
	(0.369)	(0.216)	(0.281)	(0.225)
Time trend	0.335***	0.101**	0.675***	0.602***
	(0.0461)	(0.0350)	(0.0991)	(0.0978)
SREC Price ($)	0.00145**	0.00137**	0.00106**	0.00113**
	(0.000504)	(0.000554)	(0.000526)	(0.000425)
Carve-out compliance ($)	0.00102**	0.000759$^+$	0.00188***	0.00161***
	(0.000408)	(0.000412)	(0.000486)	(0.000404)
Sales tax exemption (%)	0.509***	0.338***	0.377***	0.328***
	(0.0433)	(0.0321)	(0.0637)	(0.0718)
Rebate (d)	0.347**	0.608***	0.354**	0.384**
	(0.158)	(0.149)	(0.176)	(0.181)
RPS trend	-0.0160	-0.0232	-0.368***	-0.366***
	(0.0346)	(0.0235)	(0.0969)	(0.0962)
Income tax credit (d)	1.633***	0.502**	2.142***	2.046**
	(0.308)	(0.212)	(0.585)	(0.801)
Property tax incentive (d)	-3.006***	-1.431***	-3.167***	-2.851***
	(0.335)	(0.287)	(0.390)	(0.422)
Loan program (d)	2.417***	1.473***	3.166***	3.064***
	(0.246)	(0.216)	(0.309)	(0.273)
Solar rights (d)	-0.526**	-0.216	-1.202***	-1.177***
	(0.183)	(0.149)	(0.230)	(0.245)
Hybrid vehicle sales (%)	0.142$^+$	0.354***	0.374***	0.458***
	(0.0788)	(0.0669)	(0.0740)	(0.0737)
Democrats (%)	0.0396***	0.0154**	0.0168**	0.0128**
	(0.0115)	(0.00635)	(0.00849)	(0.00572)
Organic consumers (%)	0.0409	0.0365$^+$	-0.0170	-0.00674
	(0.0373)	(0.0204)	(0.0258)	(0.0169)
Constant	-42.09***	-24.76***	-19.55***	-13.33***
	(4.481)	(2.507)	(3.710)	(3.482)
$\hat{\sigma}_u$	1.309***		0.672***	
$\hat{\sigma}_e$	1.625***		1.630***	
Pseudo R^2		0.292		0.328
Log-likelihood	-2946.7	-3005.5	-2839.8	-2852.5

Standard errors in parentheses.
(d) for discrete change of dummy variable from 0 to 1.
$^+$ $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

In contrast to demographic factors, the policy variables introduced in model (2) are very strong predictors of residential solar PV adoption. Effects of sales tax exemptions, rebates, and loan programs are robust to specification at the 1% significance level. SREC market price and carve-out compliance payment effects are significant at the 5% level. Each of these state incentives affects the cost of installing a solar PV system. Sales tax exemptions, rebates, and loan programs decrease the up-front cost, while SREC markets decrease the amount of time it takes for a system to pay itself off.

Property tax exemption and solar rights each have a negative and significant parameter estimate across specifications. This unexpected result is consistent with Hitaj (2013), who found a negative relationship between property tax exemptions and state wind capacity. Hitaj (2013) explains this result as a data issue. Since property tax exemptions are generally one of the first policies that states use to promote solar PV adoption, the variable often corresponds with county-year observations with zero PV capacity. The same is true for solar rights policies. The model may be associating the property tax and solar rights variables with a large number of counties with zero installation. Another unexpected result is the negative significant estimate for the effect of RPS in Model (4). It is possible that RPS policies alone, holding all else constant, incentivize other renewable technologies such as wind energy, to the detriment of solar PV. This is consistent with Wiser, Barbose, and Holt (2011)'s concerns that without a solar-specific mandate, RPS programs favor a limited number of least-cost technologies.

Demand for hybrid vehicles and political party affiliation are found to be significantly related to residential solar PV demand. Voting rates for the democratic party are significant at 5% across specifications. This is strong evidence of a relationship between political party affiliation and pro-environmental preferences, and suggests that Democratic-leaning constituencies, holding all else constant, are more likely to invest in solar PV technology. The estimated effect of hybrid vehicles sales is positive and significant at 1% in model (4). Counties with a relatively high proportion of hybrid vehicles are expected to have higher residential solar PV capacity. This is further evidence of findings by Dastrup et al. (2012) which point to a positive relationship between these two "green status" consumer products. Organic food consumption, on the other hand, is not significant in any specification. There is little evidence of a link between demand for organic food and solar PV adoption.

6 Conclusion

This paper examines whether state policy incentives for residential solar PV installations are effective drivers of adoption. It is possible that solar adoption may be driven by pro-environmental preferences alone. In that case, solar policies are inefficient because adopters would have adopted solar PV absent policy incentives. Previous literature has not explored state policy effects on demand for solar PV.

Our empirical results show that policy incentives are effective in increasing solar PV capacity at the county level. We find that sales tax exemptions, income tax credits, loan financing programs and cash rebates are key drivers of growth in solar PV capacity. In addition, solar-specific mandates and a market for solar renewable energy credits increase total capacity. Not all states have specific mandates for solar energy within their RPS mandates. Our results suggest that for solar capacity to grow, solar-specific technology standards should be included in future RPS policies. We find little evidence that an RPS policy alone will drive solar PV adoption.

Contrary to previous empirical findings by Zahran et al. (2008) and Kwan (2012), we find little evidence that demographic characteristics such as age and education level are significantly related to solar PV adoption. Controlling for demographic and income differences, we find evidence that political party affiliation as well as the share of hybrid vehicle ownership within a county has a positive effect on solar adoption. This result indicates the importance of environmental preference as a predictor of solar PV demand.

The policies discussed in this paper are certain to have welfare consequences. While we do not consider the efficiency of solar PV policies, the magnitude of policy impacts estimated in this study could be used as an input to future studies examining the welfare consequences of solar PV incentives.

References

Adelaja, A., Y.G. Hailu, C.H. McKeown, and A.T. Tekle. 2010. "Effects of Renewable Energy Policies on Wind Industry Development in the US." *Journal of Natural Resources Policy Research* 2:245–262.

Andreoni, J. 1990. "Impure altruism and donations to public goods: a theory of warm-glow giving." *The Economic Journal*, pp. 464–477.

Barbose, G., N. Darghouth, and R. Wiser. 2012. "Tracking the Sun V An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998 to 2011." Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory.

Carley, S. 2009. "State renewable energy electricity policies: An empirical evaluation of effectiveness." *Energy Policy* 37:3071–3081.

Dastrup, S.R., J. Graff Zivin, D.L. Costa, and M.E. Kahn. 2012. "Understanding the Solar Home price premium: Electricity generation and Green social status." *European Economic Review* 56:961–973.

DSIRE. 2013. "Database of State Incentives for Renewables and Efficiency." Available at www.dsireusa.org.

Geographic Research Inc. 2011. "SimmonsLOCAL Consumer Survey Data." Retrieved from SimplyMap database *www.simplymap.com*.

Hausman, J.A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics* 10:33–54.

Hitaj, C. 2013. "Wind power development in the United States." *Journal of Environmental Economics and Management* 65:394–410.

Kwan, C.L. 2012. "Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States." *Energy Policy* 47:332–344.

Labay, D.G., and T.C. Kinnear. 1981. "Exploring the consumer decision process in the adoption of solar energy systems." *Journal of Consumer Research*, pp. 271–278.

Lopez, A., B. Roberts, D. Heimiller, N. Blair, and G. Porro. 2012. "US Renewable Energy Technical Potentials: A GIS-Based Analysis." *Contract* 303:275–3000.

Lutzenhiser, L. 1993. "Social and behavioral aspects of energy use." *Annual Review of Energy and the Environment* 18:247–289.

Maguire, K. 2011. "What's Powering Wind? The Role of Prices and Policies in Determining the Amount of Wind Energy Development in the United States (1994-2008)." In *2011 Annual Meeting, July 24-26, 2011, Pittsburgh, Pennsylvania*. Agricultural and Applied Economics Association.

Menz, F.C., and S. Vachon. 2006. “The effectiveness of different policy regimes for promoting wind power: Experiences from the states.” *Energy Policy* 34:1786–1796.

National Atlas of the United States. 2009. “2008 Presidential General Election, County Results.” Available at www.nationatlas.gov.

NREL. 2013. “National Renewable Energy Laboratory.” Available at openpv.nrel.gov.

Sexton, S.E., and A.E. Sexton. 2013. “Conspicuous conservation: The Prius halo and willingness to pay for environmental bona fides.” *Journal of Environmental Economics and Management*, pp. Available online.

Sherwood, L. 2012. “U.S. Solar Market Trends 2011.” Available at www.irecusa.org/publications/.

Sidiras, D.K., and E.G. Koukios. 2004. “Solar systems diffusion in local markets.” *Energy Policy* 32:2007–2018.

Smith, D. 2013. “IBISWorld Industry Report 22111e Solar Power in the US.” IBISWorld July 1-33.

Tobin, J. 1958. “Estimation of Relationships for Limited Dependent Variables.” *Econometrica*, pp. 24–36.

U.S. Energy Information Adiminstration (EIA). 2011. “Direct Federal Financial Interventions and Subsidies in Energy in Fiscal Year 2010.” Working paper.

—. 2013. “Electric Power Monthly with Data for May 2013.” Avaliable at www.eia.gov.

Wiser, R., G. Barbose, and E. Holt. 2011. “Supporting solar power in renewables portfolio standards: Experience from the United States.” *Energy Policy* 39:3894–3905.

Wooldridge, J.M. 2010. *Econometric analysis of cross section and panel data*. MIT press.

Yin, H., and N. Powers. 2010. “Do state renewable portfolio standards promote in-state renewable generation.” *Energy Policy* 38:1140–1149.

Zahran, S., S.D. Brody, A. Vedlitz, M.G. Lacy, and C.L. Schelly. 2008. “Greening local energy: explaining the geographic distribution of household solar energy use in the United States.” *Journal of the American Planning Association* 74:419–434.